Title	Locally communicative interaction framework for adaptively self-organizing mobile sensor networks
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Description	

Locally Communicative Interaction Framework for Adaptively Self-organizing Mobile Sensor Networks

Kazutaka Tatara, Geunho Lee, Hiroaki Ono, and Nak Young Chong

***Abstract*— We address the adaptive self-organization problem for mobile robotic sensors creating wireless *ad hoc* networks while adapting to topological changes. Our challenge is placed on how to exploit locally communicative interactions with minimal conditions such as locality and implicit coordination. Each sensor node organizes and updates its partially-connected network through selecting specific neighboring nodes with higher connectivity. The effectiveness of the proposed framework is verified by extensive simulations and experiments with RFID sensor networks that contain mobile sensor nodes. The most notable features of our approach include self-organization, topological adaptation, and self-healing, enabling self-organization of mobile sensor networks in an efficient way.**

I. INTRODUCTION

Many studies employing large-scale mobile sensors have been reported in fields of networking and swarm robotics. From the viewpoint of the application domain like surveillance or environmental monitoring [1], large numbers of mobile sensors can be considered as swarms of wireless sensors mounted on spatially distributed autonomous robots. Robotic sensors deployed across an area of interest may move around to improve area coverage. However, they should remain connected during their movement. Once a desired topology has formed, the network gets easily affected by node movements and/or failures. Meanwhile, the network might suffer from mutual interference if a certain number of sensors send data at the same time. Sensor networks with such latent aspects still remain several issues that need to be tackled. First, it is more essential for robotic sensors to self-organize their network while channeling their communication paths. Secondly, it is necessary to partially reflect topological changes rather than recreate from scratch and to quickly restore networks in the case of node failures. Thirdly, it is desirable to develop a communicative framework with relatively minimal conditions from the mobility point of view.

Most of the approaches for wireless sensor networks proposed so far can be broadly divided into mobility and connectivity approaches. First, it is obvious that controllable mobility for robotic sensors is one of the most important components, as the sensors need to be relocated whenever necessary. Decentralized mobility approaches [2]-[7] have been reported, mainly employing some types of force balance between inter-individual interactions. These interactions result in lattice-type configurations that offer high level coverage and multiple redundant connections, but the interactions are based on implicit communications. Secondly, connectivity is another essential factor, enabling communicative collaboration to share useful data. Connectivity approaches can be further classified into connectivity maintenance [8]-[10], optimized connectivity based deployment [11]-[13], and connectivity restoration [14]-[16] schemes. The schemes have been mainly focusing on how to maintain any desired connectivity states through mobility control, resulting in offering topologically robust networks. It has been noted that inter-node communication was established in the schemes for data exchange to improve energy efficiency and deployment accuracy. It may be necessary to further develop an integrated framework considering locality, traffic, path searching, and topological adaptation for a practical use.

This paper addresses the adaptive self-organization problem for autonomous mobile robotic sensors. There are always challenges of how to exploit communicative interactions under simple conditions such as the minimum level of locality, no requirement of long-lived state information, and implicit communication coordination. Based on such a weak model, we propose a locally communicative interaction framework (LCIF), enabling robotic sensors to organize their networks adapting to topological changes due to node movements and/or failures. Individual robots perform the proposed LCIF composed of the following three steps: local distribution acquisition, neighbor selection, and local network generation. We describe LCIF in detail, and perform extensive simulations to demonstrate its unique features such as self-organization, topological adaptation, and self-healing capabilities. As a real system implementation of mobile *ad hoc* networks, RFID tags are developed and integrated into off-the-shelf mobile robots. Both the simulation and experimental results show that robotic sensor swarms based on LCIF can self-organize themselves in an efficient way adapting to unexpected topological changes.

II. PROBLEM STATEMENT

This paper considers a swarm of mobile nodes composed of n autonomous mobile robotic sensors $r_1, r_2, \cdots, r_i, \cdots, r_n$. In the swarm, a robot r_i has its own identification but there are no initially assigned specific roles such as leader, source, sink, and gateway. All robots independently execute the same algorithm without long-lived states, but asynchronously act from other robots. Specifically, r_i can send its information to its adjacent robots within a limited communication range CB through broadcasting.

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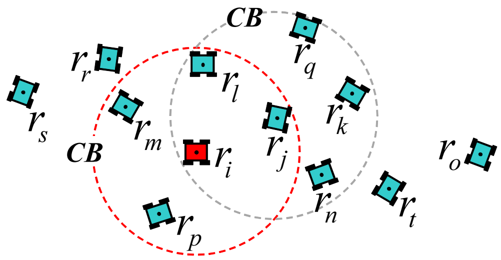


Fig. 1. Illustration of definitions and notations

Conversely, r_i can receive and/or overhear the broadcasted data.

According to whether r_i communicates to its adjacent robots r_j directly or indirectly, communicative states between r_i and r_j can be classified into 1-hop and 2-hop communications, respectively. First, the 1-hop communication is a state where r_i and r_j can directly communicate each other. Accordingly, the 1-hop communication robots with respect to r_i are simply called r_i's 1-hop robots. A set of the r_i's 1-hop robots is represented as C_i^i. If r_i has a communicative state for another robot r_s located outside its CB through a robot of C_i^1 as shown in Fig. 1, r_s is the r_i's 2-hop robot. Similarly, C_i^2 with respect to r_i denotes a set of the 2-hop robots. Moreover, r_i can select specific robots in elements of C_i^1. The selected robots are defined as r_i's neighbors $r_{i,nj}$, and a set of $r_{i,nj}$ is represented as N_i (= $\{r_{i,nj}|1 \leq j \leq m\}$ where $m > 1$).

Next, a fixed waiting time t_w is set to determine whether or not there is a connection to other nodes. Once information is broadcasted to r_j from r_i in C_i^1, r_i starts to check its t_w. If r_i receives any response from r_j during t_w, the condition with respect to r_i is defined as the connection (*i.e.*, r_i is connected to r_j by local communications). Here, a time interval from r_i's transmission to r_j's returning is represented as t_{ij}. Otherwise, the connection state is determined to be disconnected.

Based on the connection state, a local network configuration of r_i is introduced. For the local distribution in Fig. 1, we use the undirected graph $\mathcal{G}_i = \{\mathcal{V}_i, \mathcal{E}_i\}$ where $\mathcal{V}_i$ is a set of *n* vertices $\{v_1, v_2, \cdots, v_n\}$ and $\mathcal{E}_i$ is a set of edges between vertices $\mathcal{E}_i = \{(v_i, v_j)|v_i, v_j \in \mathcal{V}_i\}$. It is assumed that there is no self-loops. Specifically, we define only the 1-hop communication state between r_i and its $r_{i,nj}$ by the use of $\mathcal{G}_i$. Finally, $\mathcal{G}$ denotes a global network configuration ($\bigcup_{i=1}^{n} \mathcal{G}_i$) collecting $\mathcal{G}_i$ where n robots remain in the connection.

Three broadcasting-based communications are employed. First, to notify the existence of r_i, a hello message hel_i is broadcasted to adjacent robots r_j regularly. When r_j receives hel_i, it then replies with an acknowledgement notice ack_j. Secondly, the r_i's output message out_i of LCIF execution is given to r_j, and then r_j gives its acknowledgement notice ack_j back. Thirdly, r_i broadcasts (*i.e.*, replies) its answer message ans_i when r_i requests any information req_i from r_j. For the sake of simplicity, any messages transmitted from r_i to r_j of C_i^1 are typically represented as msg_i.

Here, we seek a decentralized solution based on only locally broadcasting. Individual robots build their local networks from the distribution of adjacent robots while removing some redundant communication links. Next, collecting the local networks also allows the robots to reach self-organization of the overall network. Despite its initial generation, this network is very changeable by robot movements. Moreover, disappearances of robots due to robot failures are another cause of changes in the network. Therefore, robots need to partially update its configuration according to changing situations. Then, we formally address the ADAPTIVE SELF-ORGANIZATION problem for a swarm of n robots based on the aforementioned model definitions as follows: *Given n robots with the above-mentioned minimal capabilities, how can individual robots self-organize their network adapting to topological changes in a decentralized way?* Consequently, we advocate that the addressed problem can be achieved by offering a self-organization, network adaptation, and self-healing solution.

III. Locally Communicative Interaction

This section describes the solution to the addressed problem. The solution, LCIF, is composed of three sequential procedures: information acquisition about the local distribution of adjacent robots, neighbor selection computation based on the acquired information, and local network generation.

A. Local Distribution Acquisition

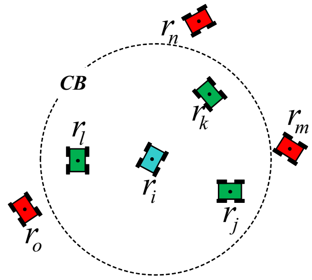
The first step in LCIF is to investigate the local configuration of adjacent robots around r_i by broadcasting and receiving including overhearing. The input is $msg_{j,k-1}$, and its outputs are $C_{i,k}^1$ and $C_{i,k}^2$. From $msg_{j,k-1}$, r_i computes $C_{i,k}^1$ and $C_{i,k}^2$. It is obvious that the inputs obtained through communications and the outputs are at time $k-1$ and k, respectively. For the sake of simplicity, we omit the notations of time k and $k-1$ afterwards.

Fig. 2-(a) illustrates a local distribution of robots. To begin, r_i broadcasts hel_i to adjacent robots r_j, then waits to receive their ack_j. Depending on the received ack_j, r_i computes C_i^1 and asks r_j of C_i^1 for their own C_j^1. After obtaining C_j^1 from r_j, r_i makes a local configuration table L_i associated according to each element of C_i^1 as shown in Fig. 2-(b). L_i represented by all elements of collections of C_j^1 (represented as $\bigcup_{j \in C_i^1} C_j^1$) indicates the direct mappings for individual elements of C_i^1. Therefore, these mappings can be regarded as a local network-configured function from C_i^1 to C_j^1, denoted by $L_i : C_i^1 \to C_j^1$.

Next, from both C_i^1 and $(\bigcup_{j \in C_i^1} C_j^1)$, C_i^2 is computed:

$$C_i^2 = (\bigcup_{j \in C_i^1} C_j^1) - C_i^1 - \{r_i\}. \quad (1)$$

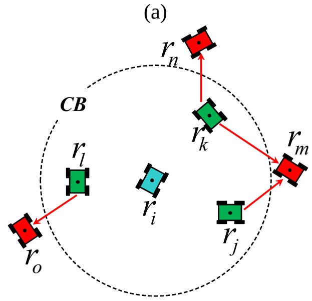
By computing C_i^2, r_i can obtain information about a configuration located outside its CB. Even though this information is still local, r_i can estimate a more extended network configured by C_i^1 and C_i^2. Ultimately, from the robot configuration in C_i^2, r_i can count the number of communication links between robots and figure out their topology configuration.



(a)

C_i^1	C_j^1
r_j	r_i, r_k, r_m
r_k	r_i, r_j, r_m, r_n
r_l	r_i, r_o

(b)



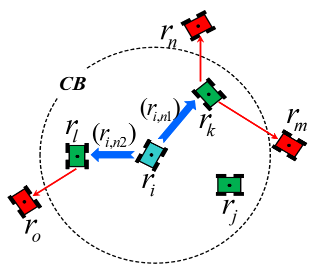
(c)

C_i^1	C_i^2
r_j	r_m
r_k	r_m, r_n
r_l	r_o

(d)

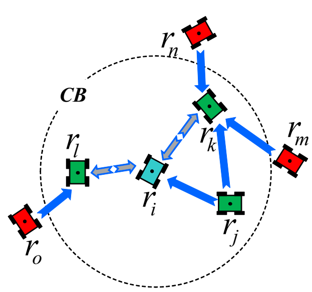
C_i^2	C_i^1
r_m	r_j, r_k
r_n	r_k
r_o	r_l

(e)



(f)

Fig. 2. Illustration of LCIF ((a) local distribution, (b) local configuration table: L_i, (c) communicative function $f_{i,12}$ from C_i^1 to C_i^2 (d) representation of $f_{i,12}$: $T_{i,12}$, (e) representation of $f_{i,21}$: $T_{i,21}$, (f) neighbor determination of r_i)



(a)

ID	N_i
r_i	$\{r_k,\ r_l\}$
r_j	$\{r_i,\ r_k\}$
r_k	$\{r_i\}$
r_l	$\{r_i\}$
r_m	$\{r_k\}$
r_n	$\{r_k\}$
r_o	$\{r_l\}$

(b)

Fig. 3. Illustration of collecting $\mathcal{G}_i$ ((a) partially-connected mesh network, (b) neighbor list of individual robots in this network)

B. Neighbor Determination

Before the explanation of the neighbor selection, we define two communicative functions $f_{i,12}$ and $f_{i,21}$ allowing r_i to examine its communicative mappings between r_j. On the one hand, $f_{i,12}$ on C_i^1 into C_i^2 is defined:

$$f_{i,12} : C_i^1 \to C_i^2. \tag{2}$$

The representation of $f_{i,12}$ is defined as $T_{i,12}$. Figs. 2-(c) and (d) illustrate $f_{i,12}$ and $T_{i,12}$, respectively. On the other hand, $f_{i,21}$ on C_i^2 into C_i^1 is given:

$$f_{i,21} : C_i^2 \to C_i^1. \tag{3}$$

Similarly, $T_{i,21}$ denotes the representation of $f_{i,21}$. More important, the composition of $f_{i,12}$ and $f_{i,21}$ is defined as a function from C_i^1 to C_i^1 through C_i^2 given by

$$f_{i,21} \circ f_{i,12}. \tag{4}$$

By the use of the composition of $f_{i,12}$ and $f_{i,21}$, r_i can estimate the connected state of its local network.

Here, the input arguments of r_i are C_i^1 and C_i^2, and its output is N_i. First, r_i examines the most mapped element of C_i^1 from robots of C_i^2. In other words, r_i investigates a robot of C_i^1 with the most mapping frequency when applying $f_{i,21}$ to each robot of C_i^2 (to obtain $C_i^1 = f_{i,21}(r)$ where $r \in C_i^2$). The most mapped element is selected as the first neighbor $r_{i,n1}$. Then, $r_{i,n1}$ of C_i^1 and its directly associated robots of C_i^2 are dropped from C_i^1 and C_i^2, respectively. After the expulsion from C_i^1 and C_i^2, individual complementary sets are defined as $C_{i,(1)}^1$ and $C_{i,(1)}^2$, respectively. Similar to the process above, r_i finds the second neighbor $r_{i,n2}$ with the most mapping from elements of $C_{i,(1)}^2$. After the determination of $r_{i,n2}$, individual complementary sets are defined as $C_{i,(2)}^1$ and $C_{i,(2)}^2$, respectively. By repeatedly doing this process until $C_i^2 = \varnothing$, r_i can select its $r_{i,nj}$ in C_i^1. And, a set of $r_{i,nj}$ selected by r_i is defined as N_i.

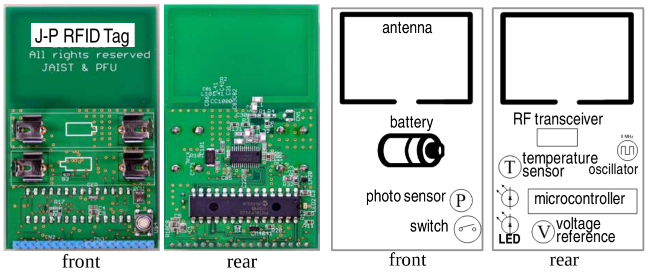
C. Local Network Generation

The r_i's input is N_i, and its output is $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$. In this paper, r_i and the selected $r_{i,nj}$ are considered as individual vertices $v_{i,i}, v_{i,n1}, \cdots, v_{i,nj}, \cdots, v_{i,nm}$, and a set of the vertices is defined as $\mathcal{V}_i$. Each edge between $v_{i,i}$ and $v_{i,nj}$ is represented as $e_{ij} = (v_{i,i}, v_{i,nj})$, and $\mathcal{E}_i$ denotes $\{e_{ij} | 1 \leq j \leq m\}$. Next, $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$ is formed with respect to r_i. Fig. 2-(f) shows the generated local network of r_i where r_k and r_l is selected as $r_{i,n1}$ and $r_{i,n2}$, respectively. Similarly, $\mathcal{G}_j = (\mathcal{V}_j, \mathcal{E}_j)$ is independently built under the same process. After the completion of $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$, r_i exchanges C_i^1 and N_i with its r_j as out_i by broadcasting.

Since r_i is connected to $r_{i,nj}$ of N_i like a $\mathcal{V}_i$-to-$\mathcal{V}_j$ connection as shown in Fig. 2-(f), this can be regarded as the star network topology. Collecting $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$ can globally reach self-organization for $\mathcal{G}$ without a centralized control scheme. When the local star networks overlap each other, the overall network can have the partially-connected mesh network topology as illustrated in Fig. 3. From the standpoint of network topology, LCIF makes it possible to take advantage of some of the network redundancy through being connected to as many adjacent robots as possible. In particular, if individual robots agree on the mutual neighbor, $\mathcal{E}$ becomes a central communication path that is connected to their many adjacent robots.

IV. Implementation of JAIST-PFU RFID Tag

For experimental studies, RFID transponders were utilized as a real wireless communication tool mounted on top of off-the-shelf mobile robots. As shown in Fig. 4, we have



(a) J-P RFID tag prototype (b) J-P RFID tag layout

Fig. 4. Hardware configuration of J-P RFID tag

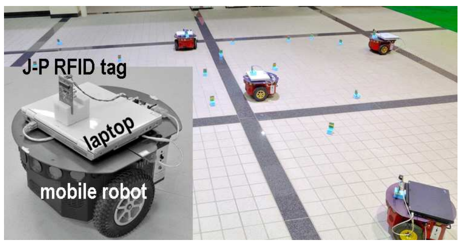
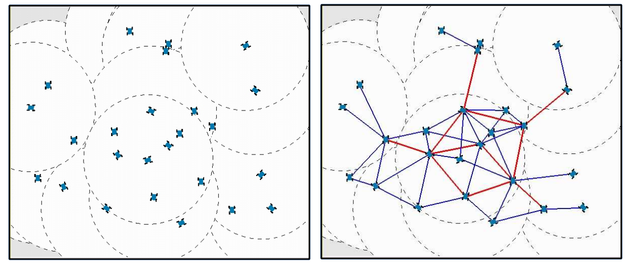


Fig. 5. Robot integration using J-P RFID tag and the distribution in an indoor environment

developed JAIST-PFU RFID transponders, which for brevity we will call J-P RFID Tag (see specific details below).

All electric devices and parts of J-P RFID Tag are located on double-sided printed wiring board where the dimension of the wiring board is 85$mm \times$ 50mm in area and 1.6mm in thickness. The electric devices are largely divided into three functions: tag control, communication, and sensing. First, Microchip PIC18F2620 microcontroller is employed as the main controller of the tag. The microcontroller is used to control radio-frequency (RF) communications, to compute the proposed algorithm, and to manage sensing components. Moreover, the microcontroller can be connected with an outside component (*e.g.*, robot) through an external communication channel (*i.e.*, RS-232c). Secondly, wireless communication components include an in-house loop antenna, Texas Instruments CC1000 RF transceiver, and Murata CSTCE_V oscillator with 14.75MHz for the transceiver. In the receiving mode, the transceiver receives Manchester encoded data at a data rate 76.8 $kBaud$ and forwards the digital demodulated data to the microcontroller. In transmitting mode of the transceiver, the RF output is broadcasted to adjacent robots through RF carrier frequencies 315MHz modulated by frequency shift key (FSK). Specifically, the built-in antenna in the printed wiring board is 131mm in length. Thirdly, National Semiconductor LM4041 voltage reference, National Semiconductor LM20 temperature sensor, and Advanced Photonix PDV-P9001 photo sensor are mounted on J-P RFID Tag, as sensing components.

Fig. 5 presents the robot integration with J-P RFID tag where a laptop PC is used as the main controller, and is placed on top of the robot. Practically, five integrated mobile robots and 18 fixed RFID tags are prepared to organize mobile sensor networks. The experimental robots and tags were distributed in an indoor environment.



(a) initial distribution of 25 robots (b) sensor network generation

Fig. 6. Simulation results for network organization

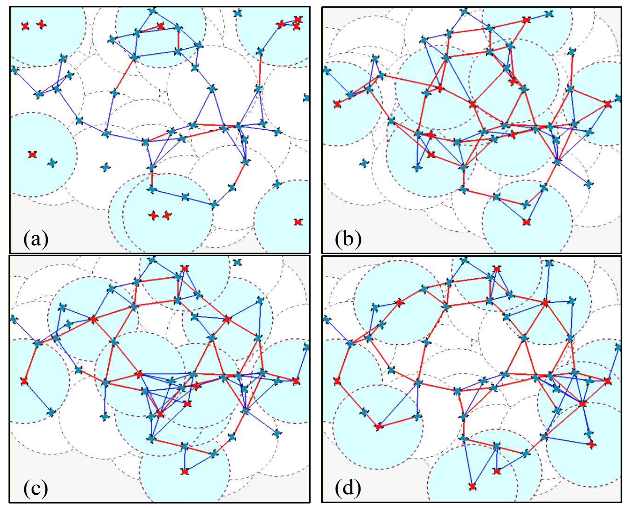


Fig. 7. Simulation result for topological adaptation where 10 red robots move arbitrarily and simultaneously and 40 blue robots remain stationary

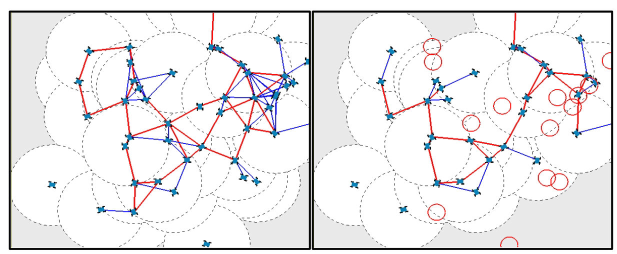
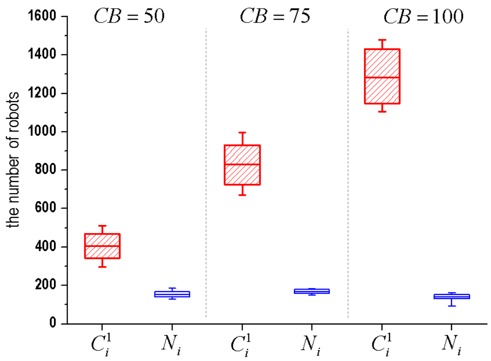


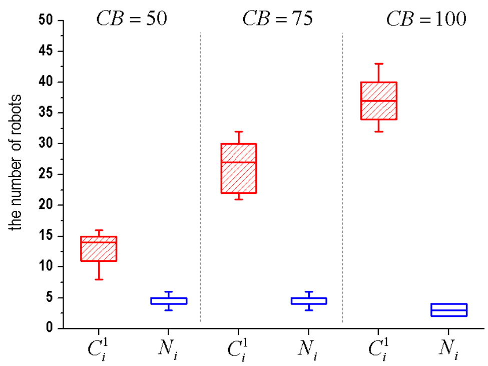
Fig. 8. Simulation results for self-healing against loss of 15 robots in 50 robot swarms

V. Simulation and Experimental Results

To evaluate the validity and the effectiveness of LCIF, we performed a series of simulations demonstrating self-organization, topological adaptation, and self-healing features. First, Fig. 6 shows simulation results for the network generation by 25 robots. In Fig. 6-(b), the blue lines mean the defined edges e_{ij} to $r_{i,nj}$ from r_i. The red bold lines indicate individual robots in agreement on the mutual neighbor selection after the network generation. It is observed that robots could organize their overall mesh network $\mathcal{G}$ by collecting local networks $\mathcal{G}_i$. Secondly, Fig. 7 presents the simulation result for topological adaptation by 50 robots. 10 red robots move arbitrarily and simultaneously to make topological changes in the generated $\mathcal{G}$, but the other robots remain stationary. Under LCIF, robots partially updated C_i^1,

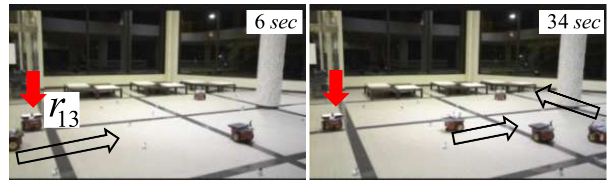


(a) data for 50 robot swarms

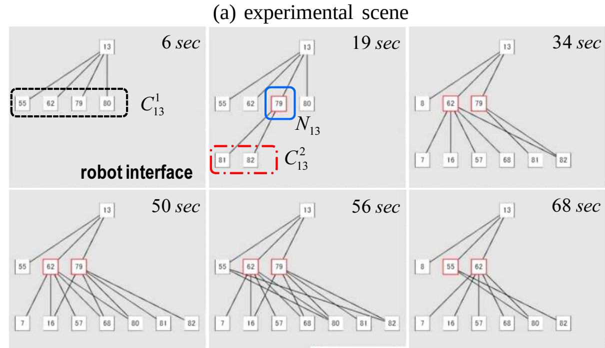


(b) data for one robot selected in the swarm

Fig. 9. Analysis results for the number of robots in C_i^1 and N_i according to radius variations of CB



(a) experimental scene



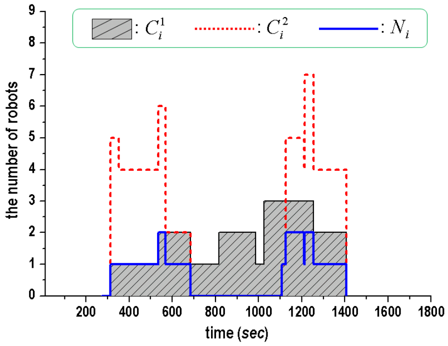
(b) topological changes of r_{13}

Fig. 10. Experimental result for topological adaptation

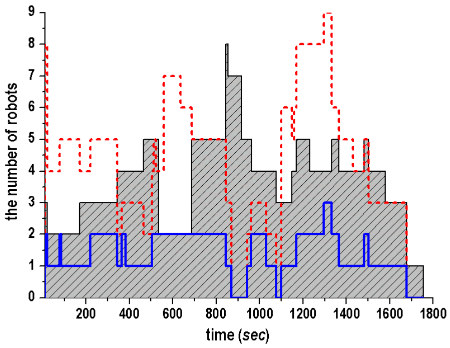
C_i^2, and N_i by the overhearing and modified a part of $\mathcal{G}$ corresponding to the changes rather than regenerated from scratch by all robots. From the result, $\mathcal{G}_i$ could adapt to topological changes according to the robot movements around r_i. It was confirmed that robot swarms could self-organize themselves while adapting to network changes. Thirdly, restoring connectivity was verified against robot disappearances due to robot failures after the initial generation of $\mathcal{G}$. 15 robots in 50 robot swarms unexpectedly failed in Fig. 8, and the same number of robots disappeared. Here, the red circles indicate the initial positions of 15 robots before their disappearances. Using broadcasted and overheard information, r_i checked the existence of adjacent robots within CB. If adjacent robots disappeared around r_i, LCIF allowed each of the robots to partially restore their local networks by partial modification.

To examine potential advantages by the neighbor selection under LCIF, we performed simulations for network organization according to radius variations of CB. For these simulations, we prepared for 30 sorts of initially different distributions by 50 robots. In our simulator, the radii of CB were set to 50, 75, and 100 units, respectively. After network organization at each simulation, the number of robots in C_i^1 and N_i for individual robots were recorded, respectively, and the numbers for C_i^1 and N_i were summed up. Specifically, a specific robot in the swarm was selected to compare the selected robot's results with those of 50 robot swarm. Fig. 9 shows the statistical analysis results where the error bars represent the 90% confidence intervals and the boxes indicate distributions of data in the range of 25-75%. As the radius of CB became larger, the number of robots in C_i^1 for individual robots increased. This is a logical conclusion from the standpoint of the 1-hop communication as mentioned in Section II. More interestingly, the trends for the number of robots in N_i are almost steady regardless of radius variations of CB. From the results, it can be inferred that the neighbor selection under LCIF was relatively unaffected by radius variations of CB. This is because r_i selects its $r_{i,nj}$ with higher connectivity after examining its local distribution. The neighbor selection has several effects on both reducing mutual interference caused by multiple information from adjacent robots and shortening the required time for channeling communication paths as well as restoring connectivity from network redundancy.

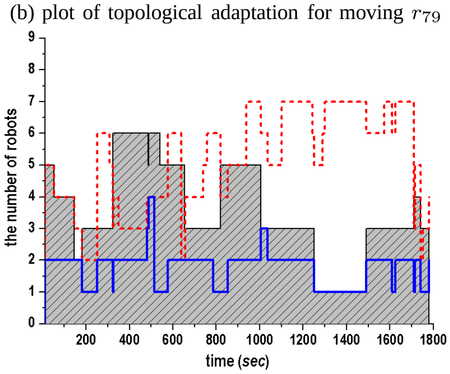
Next, two sorts of experiments were conducted to verify that robot swarms can self-organize themselves while adapting to topological changes. Fig. 10 shows the snapshots of the experiment for topological adaptation in the sensor network composed of five mobile robots equipped with the J-P RFID tag and 18 fixed J-P RFID tags. In this experiment, we examined the topological adaptation of a fixed robot r_{13} when two arbitrary robots move in the swarm. Fig. 10-(a) indicates experimental scenes and Fig. 10-(b) is states of the r_{13}'s local network configuration displaying C_i^1, C_i^2, and N_i as time went on. From the experiment, we confirmed that LCIF and its realization on the RFID tags mounted on mobile robots could be considered quite satisfactory for the practical use of mobile sensor networks. Moreover, the experimental results verified that robotic sensor swarms based on LCIF can self-organize themselves while adapting to topological changes. Fig. 11 presents an experimental result performed for half of one hour to evaluate topological adaptation and integration feasibility for LCIF and the realization of the RFID tags. In this experiment, three robots move while the others remain stationary. As compared to the variations of



(a) plot of topological adaptation for moving r_{92}



(b) plot of topological adaptation for moving r_{79}



(c) plot of topological adaptation for fixed r_{13}

Fig. 11. Experimental result performed for half of one hour to evaluate topological adaptation and the system integration feasibility

C_i^1 and C_i^2, the contours of N_{92}, N_{79}, and N_{13} became nearly flattened regardless of topological adaptation. More interestingly, when $C_i^2 = \varnothing$, N_{92} and N_{79} were empty sets. Although r_i and its r_j of C_i^1 are connected, their C_i^2 and C_j^2 are sets with no elements. Accordingly, r_i and r_j remain an isolated network.

VI. Conclusions

In this paper, the adaptive self-organization problem was addressed to organize a mobile *ad hoc* network adapting to topological changes. As our decentralized solution, we proposed LCIF allowing robots with minimal capabilities to determine neighbors with higher connectivity. Under LCIF, first, individual local networks could be generated with neighbor-based star topologies. When collecting the local networks, robot swarms could self-organize a global network with partially-connected mesh topologies. Secondly, the proposed algorithm allowed robots to self-adapt their local networks to topological changes due to robot movements and/or failures. Thirdly, the proposed neighbor selection provided the positive effects in dealing with mutual interference, channeling communication paths, and network redundancy. To demonstrate the validity and effectiveness of LCIF, extensive simulations and experiments were performed using the developed RFID tags, and the results were analyzed and compared. These results were quite encouraging, and we confirm that the proposed framework will increase the applicability of autonomous robot swarms toward mobile *ad hoc* sensor networks. We will further investigate energy-saving and connectivity enhancement issues in mobile sensor networks by integrating LCIF into the control of detailed node movement [7][9].

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